A Novel Hybrid Framework for Co-Optimization of Power and Natural Gas Networks Integrated with Emerging Technologies

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***Abstract*—This paper presents a novel hybrid information gap decision theory (IGDT)-stochastic co-optimization problem for integrating electricity and natural gas networks to minimize total operation cost with the penetration of wind energy. The proposed model considers not only the uncertainties regarding electrical load demand and wind power output but also the uncertainties of gas load demands for the residential consumers. The impact of gas load uncertainty associated with the residential consumers is more significant on the power dispatch of gas-fired plants and power system operation cost since residential gas load demands are prior than gas load demands of gas-fired units. The proposed framework is a bi-level problem that can be reduced to a one-level problem. Also, it can be solved by the implementation of a simple concept without the need for Karush-Kuhn-Tucker (KKT) conditions. Moreover, emerging flexible energy sources such as the power to gas (P2G) technology and demand response (DR) program are considered in the proposed model to facilitate integration of renewable energy sources and to decrease the total operation cost of the integrated network. Numerical results indicate the applicability and effectiveness of the proposed model under different working conditions.**

***Index Terms*—hybrid IGDT-stochastic, co-optimization of integrated gas and power system, power-to-gas (P2G) technology, demand response (DR) program, wind power.**

NOMENCLATURE

Indices

t	time periods
i	thermal units
l	natural gas loads
s	scenarios
r	wind power plants
sp	natural gas suppliers
pl	pipelines
m, n	nodes in natural gas network
st	natural gas storage systems
k	P2G technology
b, b'	buses
j	loads
L	transmission lines

Constants

NT	Number of time periods
NGL	Number of natural gas loads
NU	Number of non-gas fired units
NS	Number of scenarios
NSP	Number of gas suppliers
NST	Number of gas storages
NR	Number of wind power plants
NB	Number of buses
GU	Number of gas-fired units
P_i^{max}, P_i^{min}	Min/Max capacity of thermal unit i (MW)
RU_i, RD_i	Ramp up/down thermal unit i (MW)
T_i^{On}, T_i^{Off}	Minimum up/down time of unit i (h)
X_L	Reactance of line L (Ohm)
PF_L^{max}	Maximum capacity of line L (MW)
$D_{j,t,s}$	Expected hourly load (MW)
C_{pl}	Constant of pipeline pl (kcf/Psig)
$\pi_m^{\max}$, $\pi_m^{\min}$	Max/Min pressure (Psig)
$U_{\text{sp}}^{\max}$, $U_{\text{sp}}^{\min}$	Max/Min natural gas injection (kcf)
$L_{\text{l}}^{\max}$, $L_{\text{l}}^{\min}$	Max/Min natural gas load (kcf)
$U_{\text{s,max}}^{\text{out}}$, $U_{\text{s,max}}^{\text{in}}$	Max release/store capacity of gas storage (kcf)
η_s^{in}, η_s^{out}	Storing/releasing efficiency of gas storage
η_k^{p2g}	Efficiency of P2G technology
$E_s^{\max}$, $E_s^{\min}$	Max/min gas stored in gas storage system (kcf)
$C_{\text{sp}}^{\text{SUP}}$	Operation cost of natural gas supplier sp ($)
$C_{\text{st}}^{\text{GST}}$	Operation cost of gas storage ($)

Decision variables

F_i^C	Cost function of thermal unit i
SU_i, SD_i	Start-up / Shut-down cost of unit i
$F_{i,t,s}^{\text{gas unit}}$	Fuel function of gas-fired unit i
$F_{\text{pl},t,s}$	Gas flow on pipe pl
$P_{i,t,s}$	Dispatch of unit i
$I_{i,t,s}$	Binary on/off status indicator of unit i
$\pi_{m,t,s}$	Pressure of natural gas node m
$U_{\text{sp},t,s}$	Gas delivery of supplier
$X_{i,t-1}^{\text{on}}$, $X_{i,t-1}^{\text{off}}$	On/Off time of unit i
$LG_{\text{m,t,s}}$	Natural gas load connected to node m
$P_{r,t,s}$	Dispatch of wind power
$PF_{L,t,s}$	Line flow at line L
$\delta_{b,t,s}$	Voltage angle of network buses

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$P^{p2g}_{k,t,s}$	Dispatch of P2G technology
$U^{p2g}_{k,t,s}$	Natural gas production of P2G technology
$U^{\text{in}}_{\text{st},t,s}$, $U^{\text{out}}_{\text{st},t,s}$	Storing/Releasing rate of gas storage
$E_{\text{st},t,s}$	Natural gas stored in gas storage system
$DR_{j,t,s}$	Adjustable load
$d^{\text{DR}}_{j,t,s}$	Load after implementation of DR program
$DR^{max}_{j,t}$	Load shiftable factor as present
π_s	Probability of each scenario

I. Introduction

THE penetration of renewable energy sources such as wind turbines and photovoltaics have been dramatically increased due to concerns on the reduction of fossil fuels and global issues of greenhouse gases emissions [1], [2]. The speculation of 2182 TWh wind power generation by 2030, reported by International Energy Agency (IEA), highlights such contribution of renewable sources in supplying demand in power systems [3]. However, the variation of wind power generation with respect to the forecasted amount and uncertain nature of such energy source makes it important to find an appropriate strategy to control such situations. A practical solution for handling the above-mentioned issue is to develop natural gas-fired generation plants, which can not only of decrease emissions of pollutant gases up to 60% compared to the coal-fired plants, but also deal with the variation of renewable energy generation by high ramp-rates and fast start-up characteristics [4]. In addition, introduction of shale gas production technology in U.S.A had a significant effect on reducing the natural gas price leading to extending gas combined-cycle plants. The statistics proves considerable alteration in employing gas-fired plants in power systems such as growth rate of gas consumption in U.S.A for power generation to 39% in 2012. The impactful role of natural gas is observed not only in expansion of natural gas-fired plants but also in employment of power to gas (P2G) technology. P2G as a novel approach for storing energy as natural-gas plays an important role for accommodation of renewable energy variability [5]. Accordingly, a heated topic on integrated energy systems has enlivened the previous studies regarding interdependency of electrical and gas networks according to the influence of natural gas-fired units and P2G systems.

Integrated electricity and gas networks are hotly studied in recent publications focusing on co-optimization models of such networks, as well as technologies developed such as P2G system and demand response (DR) programs. Several works have concentrated on proposing approaches for relaxation of coupling constraints including a convex relaxation model [6], Lagrangian relaxation [7], Benders decomposition [8], and alternating direction method of multipliers [9]. A security-constrained model for integrated gas and electricity networks has been proposed investigating the effect of gas pipelines disruptions and power transmission losses [10]. A bi-level framework for co-optimization of integrated gas and electricity networks has been introduced in [11] with two agents, where the former agent aims at minimizing the operation cost of the integrated network, and the latter one seeks to maximize the profit of private owners. A bi-level model for the optimal operation of integrated gas and electricity networks is presented in [12], which intends to study the operation of the electricity network and supplying the gas network in upper-level and lower-level, respectively. The authors have analyzed the impact of cooperation of gas-fired power generation plants in integrated networks and energy market considering gas network constraints [13]. The role of the P2G system in optimal management of integrated networks is studied proposing a robust framework [14].

Information gap-decision theory (IGDT) is introduced as a high-performance modeling concept for studying uncertainties of systems' parameters and data, which does not need the probability distribution function of the uncertain parameters in contrast with conventional methods such as Monte Carlo simulation method and scenario-based programming procedure. Moreover, one other advantage of the IGDT is to provide flexible different strategies for the operator since the radius upper bound of the uncertain parameter is not needed to be known when employing this method. In other words, IGDT determines the maximum uncertainty radius of the uncertain parameters by satisfying the objective function in the predefined interval. Notable efforts have been made in the area of studying uncertainty in electrical energy networks such as bidding strategies in the power systems [15], unit commitment [16] and restoration of electrical distribution systems [17], self-scheduling of generation companies [18].

Table I indicates the comparison of the main contributions of the literature and the proposed model in studying the integrated gas and electricity networks by providing summarized cases on the remarkable contribution of models. In comparison with the literature, this study presents a new IGDT-stochastic-based model for the optimal operation of integrated power and gas systems in the presence of wind power and emerging technologies. The proposed model makes it possible to deal with uncertainties associated with both power and gas systems in contrast with the recent studies, where robust and stochastic modeling methods are applied to investigate the uncertain parameters in optimal operation of integrated gas and power systems, and the uncertainties of the gas network are not taken into account. The main contributions of this paper can be summarized as follows:

1) The proposed hybrid IGDT-stochastic framework takes advantages of both IGDT and stochastic programming methods, which makes the use of two risk-seeker and risk-averse strategies for modeling the uncertainty of residential gas load. This is effective in increasing the flexibility of the decision-making process of the network operator in overcoming such uncertainties, however, the robust model only considers the undesirable impact of the uncertain parameter. Also, the proposed hybrid method aims to determine the forecast error of uncertain parameter (i.e., residential gas load) with respect to its predicted value, where the error is obtained by the desirable operation cost of the network operator. Accordingly, the uncertainty radius is not known in contrast to the robust optimization method.
2) The presented hybrid IGDT-stochastic model is a bi-level problem, which can be changed to a single-level problem and can be solved with a simple approach without

requiring the KKT conditions.

3) The uncertainties of both gas and power networks are considered in the proposed hybrid model. On the contrary, recent studies considered only the uncertainties of the power system. The proposed hybrid IGDT-stochastic model addresses the uncertainties regarding wind power output and power and residential gas load demands, where the Montel Carlo simulation method is applied for modeling the power system uncertainties and IGDT is employed to deal with the uncertainty of natural gas system.
4) The emerging technologies in power and gas networks such as DR programs and P2G technology are taken into account to boost the flexibility of the integrated network. Moreover, the influence of such technologies is investigated in increasing and decreasing the penetration of wind power and the operation cost of the system, respectively.

II. PROBLEM FORMULATION BASED ON HYBRID IGDT-STOCHASTIC APPROACH

The mutual connection of gas and electricity networks has been increased considering the increment of integrated gas-fired plants in the power systems. Accordingly, the solution of optimal management regarding the integrated network needs to consider not only the uncertain parameters of the electricity network but also the uncertainties associated with the gas network since the consideration of uncertainties associated with the gas network parameters plays a significant role in the commitment of gas-fired plants in power systems. In this paper, the uncertainties of electrical load demand, wind power output, and the residential gas load consumer have been estimated by IGDT approach.

A. Problem formulation based on Stochastic programming

In this section, the co-optimization problem of integrated gas and electricity networks is explained based on a stochastic model that is performed by Monte Carlo simulation method. The objective function and constraints are defined as follows:

1) Objective function: The main objective of the presented model is to minimize the operation cost in the integrated networks in presence of wind energy and emerging technologies. Equation (1) indicates the objective function of the proposed model, which is defined as the costs associated with coal-fueled generation units, natural gas-fired plants and operation cost of the gas storage system.It is notable that the cost of gas-fired units is considered in the cost of gas suppliers.

$$\mathbf{min} \sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \begin{bmatrix} \sum_{i=1}^{NU} \left[F_i^C \left(P_{i,t,s} \right) + SU_{i,t} + SD_{i,t} \right] \\ + \sum_{sp=1}^{NSP} C_{sp}^{SUP} \, U_{sp,t,s} \\ + \sum_{st=1}^{NST} C_{st}^{GST} \, U_{st,t,s}^{out} \end{bmatrix} \tag{1}$$

The objective function should be optimized considering several constraints including coal-fueled and natural gas-fired plants, natural gas storage, P2G system, DR program, electrical network and gas systems, which are described in the following.

2) Unit commitment constraints: The power generated by the non-gas fired and gas-fired plants should be restricted to the upper and lower bounds as stated in (2). Ramp-up and ramp-down rates for generation plants are formulated as (3) and (4), respectively. The relation between auxiliary variables applied in ramp-up and ramp-down rates are pointed out in (5) and (6). Equations (7) and (8) indicate that each generation plant should be limited by minimum up-time and down-time constraints. Also, (9)-(12) show the start-up and shut-down cost of non-gas-fired units and gas consumption associated with start-up and shut-down of gas-fired plants.

$$P_i^{\min} I_{i,t} \leq P_{i,t,s} \leq P_i^{\max} I_{i,t} \tag{2}$$

$$P_{i,t,s} - P_{i,t-1,s} \leq (1 - Y_{i,t}) R_i^{up} + Y_{i,t} P_i^{\min} \tag{3}$$

$$P_{i,t-1,s} - P_{i,t,s} \leq (1 - Z_{i,t}) R_i^{dn} + Z_{i,t} P_i^{\min} \tag{4}$$

$$Y_{i,t} - Z_{i,t} = I_{i,t} - I_{i,t-1} \tag{5}$$

$$Y_{i,t} + Z_{i,t} \geq 1 \tag{6}$$

$$\left(X_{i,t-1}^{on} - T_i^{on} \right) \left(I_{i,t-1} - I_{i,t} \right) \geq 0 \tag{7}$$

$$\left(X_{i,t-1}^{off} - T_i^{off} \right) \left(I_{i,t} - I_{i,t-1} \right) \geq 0 \tag{8}$$

$$SU_{i,t} \geq su_i \left(I_{i,t} - I_{i,t-1} \right) \quad i \notin GU \tag{9}$$

$$SD_{i,t} \geq sd_i \left(I_{i,t-1} - I_{i,t} \right) \quad i \notin GU \tag{10}$$

$$SUG_{i,t} \geq sug_i \left(I_{i,t} - I_{i,t-1} \right) \quad i \in GU \tag{11}$$

$$SDG_{i,t} \geq sdg_i \left(I_{i,t-1} - I_{i,t} \right) \quad i \in GU \tag{12}$$

3) Demand response program constraints: In this paper, the proposed DR program is modeled as shiftable approach. In this concept, the responsive loads can be programmed to run within a particular time due to lower electricity prices. Equation (13) demonstrates the network load after the execution of the DR program. Equation (14) presents the limitation of the shiftable load at each hour. Equations (15) and (16) indicate the boundary of the variation rate of sensitive loads to price in continuous time intervals. Finally, (17) shows the curtailed load as the determined time should be shifted to another time.

$$d_{j,t,s}^{DR} = D_{j,\,t,s} + DR_{j,t,s} \tag{13}$$

$$|DR_{j,t,s}| \leq DR_{j,t}^{\max} D_{j,t,s} \tag{14}$$

$$d_{j,t,s}^{DR} - d_{j,t-1,s}^{DR} \leq \Delta d_j^{up} \tag{15}$$

$$d_{j,t-1,s}^{DR} - d_{j,t,s}^{DR} \leq \Delta d_j^{dn} \tag{16}$$

$$\sum_{t=1}^{NT} DR_{j,\,t,\,s} = 0 \tag{17}$$

4) Power system security constraints: Equation (18) shows that the power balance of the network should be taken into consideration to ensure the supply of power load demand by the generation plants and power flow through system lines. Moreover, (19) and (20) demonstrate DC power flow and the line capacity limitation of DC power flow, respectively.

$$\sum_{i=1}^{NU_b} P_{i,t,s} + \sum_{r=1}^{NR_b} P_{r,t,s} - \sum_{k=1}^{NK_b} P_{k,t,s}^{p2g} - \sum_{j=1}^{NJ_b} d_{j,t,s}^{DR} = \sum_{l=1}^{NL_b} PF_{L,t,s} \tag{18}$$

$$PF_{L,t,s} = \frac{\delta_{b,\,t,s} - \delta_{b',\,t,s}}{x_L} \tag{19}$$

$$-PF_L^{\max} \leq PF_{L,t,s} \leq PF_L^{\max} \tag{20}$$

TABLE I: Comparison of the literature with the current work

Reference	Co-optimization	Uncertainties				Uncertainty modeling	Flexible Technologies	
		Gas load	Electric load	Wind	Line outage		P2G	DR
[19]			✓		✓	Stochastic		
[20]			✓	✓		Stochastic		
[21]			✓	✓		Stochastic		✓
[14]	✓		✓	✓		Robust	✓	
[22]	✓		✓	✓		Robust	✓	
[23]	✓				✓	Robust		
[24]	✓		✓	✓	✓	Robust		
[25]	✓		✓	✓		Stochastic		
Proposed	✓	✓	✓	✓		IGDT-Stochastic	✓	✓

5) Natural gas storage: The natural gas storage system has been considered in this study to inject the storage gas to the integrated network for flattening the gas load profile. The gas storage unit can be utilized as an appropriate option when the gas load cannot be supplied due to the limitation of the gas capacity supplier or gas transmission pipeline capacity. Equations. (21) and (22) restrict the storage and release capacity of the gas storage. The storage balance and capacity limitations are provided by (23) and (24), respectively. Also, (25) and (26) meet the initial and final requirements of the natural gas storage unit.

$$0 \le U_{st,t}^{out} \le U_{st,\max}^{out} \tag{21}$$

$$0 \le U_{st,t}^{in} \le U_{st,\max}^{in} \tag{22}$$

$$E_{st,\,t,\,s} = E_{st,\,t-1,\,s} + \eta_{st}^{in} U_{st,\,t,\,s}^{in} - \frac{U_{st,\,t,\,s}^{out}}{\eta_{st}^{out}} \tag{23}$$

$$E_{st}^{\min} \le E_{st,\,t,\,s} \le E_{st}^{\max} \tag{24}$$

$$E_{st,\,0,\,s} = E_{st,\,\text{intial},\,s} \tag{25}$$

$$E_{st,\,0,\,s} = E_{st,\,end,\,s} \tag{26}$$

6) Natural gas network constraints: The natural gas flow through the gas pipeline is provided in (27) and (28), which is a function of gas pressure at two ends of the pipeline. Equation (29) specifies the connection of residential gas demands and gas-fired units to each node of the gas system. The consumption of gas by gas-fired generation plants is formulated in (30), which is connected to a gas storage unit. Also, (31) considers the P2G system as a gas supplier. The limitation of gas supplier and node pressure are mentioned in (32) and (33). Finally, (34) indicates the natural gas balance considering gas suppliers, gas load, gas injected by P2G system, and gas flow through the gas pipeline.

$$F_{pl,t,s} = sgn(\pi_{m,t,s}, \pi_{n,t,s})\, C_{m,n} \sqrt{\left|\pi_{m,t,s}^2 - \pi_{n,t,s}^2\right|} \tag{27}$$

$$sgn(\pi_{m,t,s}, \pi_{n,t,s}) = \begin{cases} 1 & \pi_{m,t,s} \ge \pi_{n,t,s} \\ -1 & \pi_{m,t,s} \le \pi_{n,t,s} \end{cases} \tag{28}$$

$$LG_{m,t,s} = \sum_{g=1}^{NG_m} RG_{g,t} + \sum_{i=1}^{NGU_m} F_{i,t,s}^{gas} \qquad i \in GU \tag{29}$$

$$\begin{aligned} F_{i,t,s}^{gas} &= \alpha_i + \beta_i P_{i,t,s} + \gamma_i P_{i,t,s}^2 + SUG_{i,t} + SDG_{i,t} \\ &+ \textstyle\sum_{s=1}^{NS_i} (U_{s,\,t,s}^{in} - U_{s,\,t,s}^{out}) \qquad i \in GU \end{aligned} \tag{30}$$

$$U_{k,t,s}^{p2g} = \varphi\, P_{k,t,s}^{p2g}\, \eta_k^{p2g} \tag{31}$$

$$\sum_{sp=1}^{NSP_m} U_{sp,t,s} - LG_{m,t,s} + \sum_{k=1}^{Nk_m} U_{k,t,s}^{p2g} = \sum_{pl=1}^{NPL_m} F_{pl,t,s} \tag{32}$$

$$\pi_m^{\min} \le \pi_{m,t,s} \le \pi_m^{\max} \tag{33}$$

$$U_{sp}^{\min} \le U_{sp,t,s} \le U_{sp}^{\max} \tag{34}$$

7) Hybrid IGDT-stochastic framework: In this paper, an IGDT-stochastic model is proposed to minimize the total operation cost, which is a co-optimization problem for integrating electricity and natural gas networks. The proposed hybrid model is described in algorithm. (1) in details. Moreover, it differs from the stochastic programming method in three aspects: 1) In stochastic programming only based on scenarios, the load demand is a function of scenarios, where the increment of the calculations has a direct relationship with the number of scenarios. On the other hand, IGDT requires no scenario generation. 2) In stochastic programming only based on scenarios, the probability distribution of uncertain parameter is needed to model; however, such function is not required in IGDT model. 3) In the proposed model, the decision makers can decide on two various strategies when encountering with the uncertain parameter, which increases the flexibility of decision making in response to the uncertainties of the system parameters.

Algorithm 1 THE PROPOSED HYBRID IGDT-STOCHASTIC FRAMEWORK

Require: Data collection
Data collection regarding power demands, wind power and residential gas loads.

1) **Scenario Generation (uncertainty methods)**
   Application of data and probability distribution function for scenario generation of power demands and wind power
2) **Scenario Reduction**
   Application of Fast-Backward approach for reducing the number of scenarios
3) **Stochastic programming** (Eqs. (1)-(34))
   Stochastic programming
4) **Calculation** (Eq. (1))
   Calculation of the operation cost
5) **Uncertainty modeling** (Eqs. (35)-(53))
   Modeling the uncertainty of residential gas load using IGDT method
6) **Risk-averse: Eqs. (36)-(44)**
   Application of risk-averse strategy
7) **while** $d_r = d_{r-1}$ **do** Increment of cost deviation factor: $d_r = d_{r-1}$, r=1,..., NR obtaining optimal robustness factor
8) **end while**
9) **Risk-seeker** (Eqs. (45)-(53))
   Risk-seeker strategy (opportunistic)
10) **while** $d_p = d_{p-1}$ **do** Decrement of cost deviation factor: $d_p = d_{p-1}$, p=1,..., NP obtaining optimal opportunistic factor Save the variables
11) **end while**

The uncertainty in an optimization problem using IGDT is modeled as (35), where U is the set of input uncertain parameter. $\overline{\Psi}$ is the predicted amount of the uncertain parameter Ψ. Also, the deviation lower bound of the uncertain parameter from the predicted amount is defined by ϵ . This parameter is introduced as an uncertain unknown radius of the decision maker.

$$U = U(\bar{\Psi}, \varepsilon) = \left\{ \Psi : \left| \frac{\Psi - \bar{\Psi}}{\bar{\Psi}} \right| \leq \varepsilon \right\} \tag{35}$$

In the proposed hybrid IGDT-stochastic model, the system operator can present two strategies to control the uncertainty of the system, which is discussed as follows:

8) Risk-averse strategy: In this strategy, the operator separates the uncertain parameter having an undesirable effect on the objective function. Given that the main goal of this paper is to reduce the total operation cost, the risk-averse utilizes a schedule to overcome the decrement of operation cost resulting from the undesirable variation of the residential gas load from the predicted value. Hence, the mathematical model of the risk-averse can be formulated as follows:

$$\alpha(X, \Delta_C) = Max \left\{ \varepsilon : \left(\underset{\Psi \in U(\bar{\Psi}, \varepsilon)}{Max} \quad OF \leq \Delta_C = (1 + d_r) OF_b \right) \right\} \tag{36}$$

Δ_C defines the critical value of operation cost. d_r is critical level of operation cost. Also, OF_b is the operation cost in the base condition, where the uncertain parameter has no variation concerning the predicted value. Moreover, renewable sources are not considered in the base condition. X is also an array containing the decision variables. The main aim of implementing the IGDT model for the operator is to decrease the radius of the uncertain parameter between the uncertain and forecasted values, which is proposed as a bi-level problem in (37)-(40).

$$\alpha = Max\ \varepsilon \tag{37}$$

Subject to:

$$\max \sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \left[\begin{array}{l} \sum_{i=1}^{NU} \left[F_i^C(P_{i,t,s}) + SU_{i,t} + SD_{i,t} \right] \\ + \sum_{sp=1}^{NSP} C_{sp}^{SUP}(U_{sp,t,s}) \\ + \sum_{st}^{NST} C_{st}^{GST} U_{st,t,s}^{out} \end{array} \right] \leq \Delta_C \tag{38}$$

$$(1 - \varepsilon) \hat{RG}_{g,t} \leq RG_{g,t} \leq (1 + \varepsilon) \hat{RG}_{g,t} \tag{39}$$

$$Eqs.\ (2) - (34) \tag{40}$$

The reduction of the residential gas load has a positive influence on operation cost. In other words, the increment of the gas load has an undesirable effect. Accordingly, in the proposed risk-averse model, the maximum operation cost is related to the condition that the gas load is increased with respect to the predicted value. Thus, the proposed bi-level model in (37)-(40) is converted to a single-level problem as pointed out by (41)-(44).

$$\alpha(X, \Delta_C) = Max\ \varepsilon \tag{41}$$

Subject to:

$$\sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \left[\begin{array}{l} \sum_{i=1}^{NU} \left[F_i^C(P_{i,t,s}) + SU_{i,t} + SD_{i,t} \right] \\ + \sum_{sp=1}^{NSP} C_{sp}^{SUP}(U_{sp,t,s}) + \sum_{st}^{NST} C_{st}^{GST} U_{st,t,s}^{out} \end{array} \right] \leq \Delta_C \tag{42}$$

$$LG_{m,t,s} = \sum_{g=1}^{NG_m} RG_{g,t}(1 + \varepsilon) + \sum_{i=1}^{NGU_m} F_{i,t,s}^{gas} \tag{43}$$

$$Eqs.\ (2) - (28)\ \ and\ \ Eqs.\ (30) - (34) \tag{44}$$

9) Risk-seeker (RS) strategy: It should be mentioned that the uncertainty of parameters does not always have the detrimental effect on the objective function. Consequently, RS strategy is introduced for taking into account the situation that the objective function takes advantage of positive effect of the uncertain parameter. Actually, the aim of the decision maker is to provide lower objective function than the basic condition value. The formulation of the objective function regarding the RS strategy (called opportunity function) is stated as follows:

$$\beta(X, \Delta_C) = \min \left\{ \varepsilon : \left(\underset{\Psi \in U(\bar{\Psi}, \varepsilon)}{Min} \quad OF \leq \Delta_C = (1 - d_p) OF_b \right) \right\} \tag{45}$$

$$\beta(X, \Delta_C) = Min\ \varepsilon \tag{46}$$

Subject to:

$$\min \sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \left[\begin{array}{l} \sum_{i=1}^{NU} \left[F_i^C(P_{i,t,s}) + SU_{i,t} + SD_{i,t} \right] \\ + \sum_{sp=1}^{NSP} C_{sp}^{SUP}(U_{sp,t,s}) \\ + \sum_{st}^{NST} C_{st}^{GST} U_{st,t,s}^{out} \end{array} \right] \leq \Delta_C \tag{47}$$

$$(1 - \varepsilon) \hat{RG}_{g,t} \leq RG_{g,t} \leq (1 + \varepsilon) \hat{RG}_{g,t} \tag{48}$$

$$Eqs.\ (2) - (34) \tag{49}$$

d_p is optimistic level of operation cost. As previously mentioned, the reduction of the residential gas load has a positive impact on the operation cost. Therefore, in the introduced risk-seeker framework, the minimum operation cost belongs to the situation that the gas load is decreased regarding the forecasted amount. Consequently, the single-level problem in (50)-(53) can be presented instead of the proposed bi-level model in (45)-(48):

$$\beta(X, \Delta_C) = Min\ \alpha \tag{50}$$

Subject to:

$$\sum_{t=1}^{NT} \sum_{s=1}^{NS} \pi_s \left[\begin{array}{l} \sum_{i=1}^{NU} \left[F_i^C(P_{i,t,s}) + SU_{i,t} + SD_{i,t} \right] \\ + \sum_{sp=1}^{NSP} C_{sp}^{SUP}(U_{sp,t,s}) + \sum_{st}^{NST} C_{st}^{GST} U_{st,t,s}^{out} \end{array} \right] \leq \Delta_C \tag{51}$$

$$LG_{m,t,s} = \sum_{g=1}^{NG_m} RG_{g,t}(1 - \varepsilon) + \sum_{i=1}^{NGU_m} F_{i,t,s}^{gas} \tag{52}$$

$$Eqs.\ (2) - (28)\ \text{ and }\ Eqs.\ (30) - (34) \tag{53}$$

III. CASE STUDY AND SIMULATION RESULTS

The introduced framework has been implemented on a test system for determining the efficiency of the model. The proposed case study, which is depicted in Fig. 1, is an integrated 6-bus electrical network to a 6-node gas system. The coefficients of operation cost and operational characteristics of the thermal plants are adapted from [19]. The information of forecasted wind power generation, the electricity load, and residential gas load demands are demonstrated in Fig. 1.

The proposed mixed integer non-linear programming (MINLP) model is solved in GAMS environment using DICOPT solver. The forecasted error of uncertain parameters is based on a normal distribution function with a 5% and 10% standard deviation for the electric load and wind turbines, respectively. A thousand scenarios are generated using Monte Carlo simulation approach, which is reduced to five scenarios utilizing Fast-Backward approach. Four case studies are taken into account to ensure the practicality and effectiveness of the proposed framework as follows:

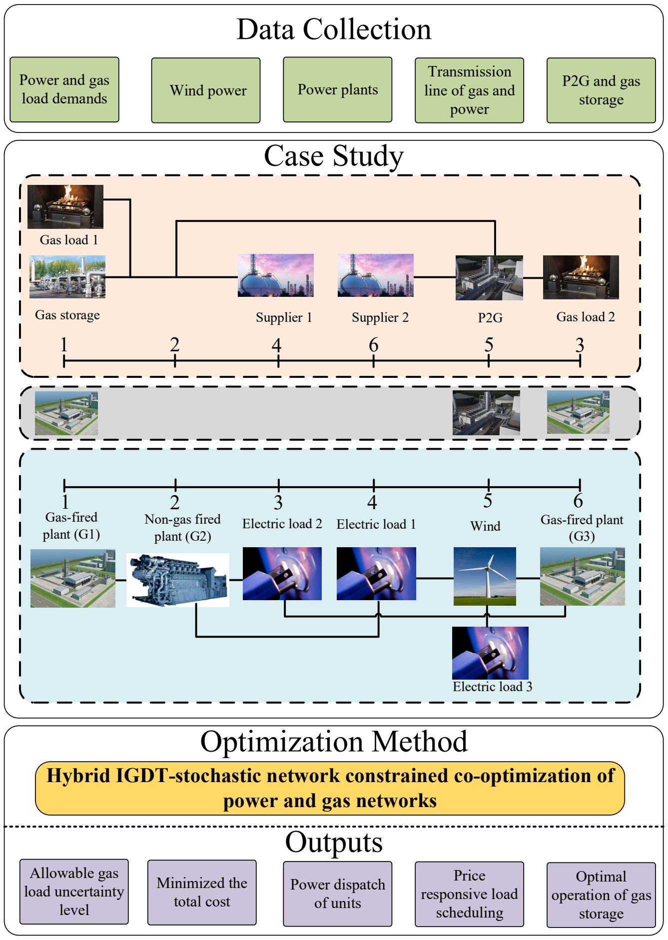

Fig. 1: The proposed case study

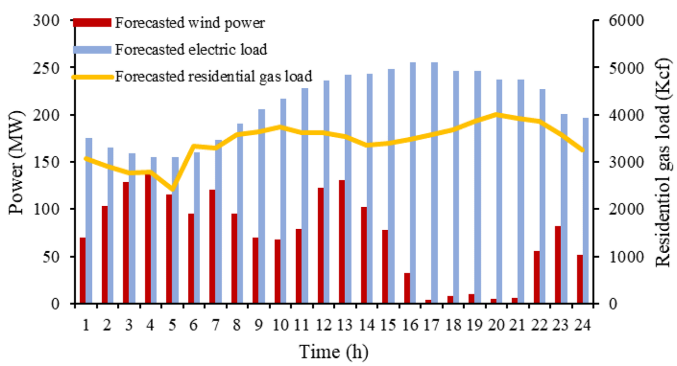

Fig. 2: Forecasted wind power, electric load and residential gas load

A. *Case 1: stochastic co-optimization of integrated gas and electricity networks without considering P2G technology and DR program*

In this case, the uncertainties of the integrated network include the power generation of the wind turbines and the electric load of the network. The interaction between the wind power dispatch and natural gas storage without considering P2G is shown in Fig. 3. The analysis of this figure proves the extreme dependency of the gas and power networks to each other. In other words, the gas storage stored the natural gas when wind power dispatch is increased, and injected the stored gas to node 1 of the gas network when the wind power dispatch

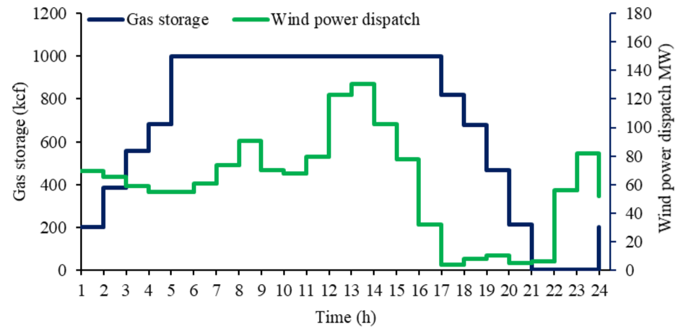

Fig. 3: Relation between natural gas storage and wind power dispatch

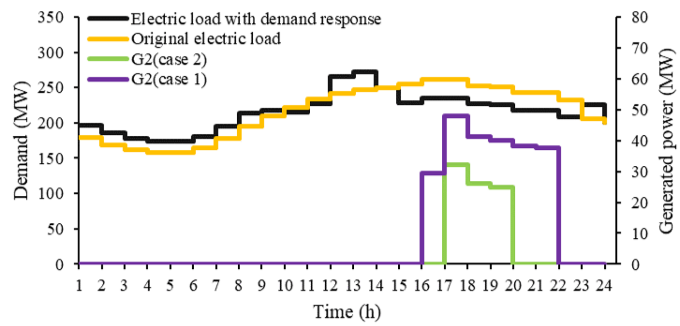

Fig. 4: The impact of DR program on electricity load profile and power dispatch of unit G2

is decreased. Accordingly, the natural gas storage makes it possible to supply gas to the gas-fired plant G1 in peak hours when encountering gas supply shortage in the gas network. This is effective in cooperation of high-cost generation plants and decrement of the system operation cost. The operation cost of the system in this case study is equal to \$114604.998.

B. *Case 2: stochastic co-optimization of integrated gas and electricity networks considering DR program*

In this case study, the effect of DR programs is investigated on the operation of integrated gas and power networks. The load participation factor (LPF) of the DR program is assumed to be 10%. The impact of the DR program on the load profile concerning the system and power dispatch of the expensive generation plant G2 is depicted in Fig. 4. As seen in this figure, the electric load demand is shifted from on-peak hours to off-peak hours, which leads to the participation reduction of plant G2 in supplying electric load demand. It should be mentioned that the generation of plant G2 is decreased to 82.933 MWh with regards to the production of 320.85 MWh in Case 1. Table II indicates the influence of the application of DR program with various LPF on the operation cost of the power and gas systems. As it is obvious from the results, the operation cost of power and gas systems and consequently total operation cost is reduced. Moreover, by enhancing the LPF, the wind power dispatch is increased due to the increment of load demand in off-peak hours.

TABLE II: The impact of LPF of DR on the operation cost and dispatched wind power

LPF in DR program (%)	2	4	6	8
Gas system operation cost ($)	134545.4	134554.14	134689.51	134810.37
Power system operation cost ($)	10207.96	8067.604	6974.621	5962.375
Total operation cost ($)	143744.91	142621.74	141664.13	140772.75
Dispatched wind power (MWh)	1451.133	1471.767	1492.364	1511.973

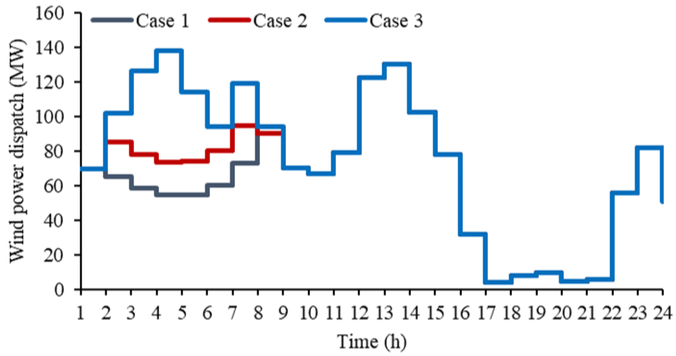

Fig. 5: Expected wind power dispatch for different cases

C. *Case 3: stochastic co-optimization of integrated gas and electricity networks considering P2G technology and DR program*

In this situation, P2G technology and DR program are considered simultaneously. Fig. 5 and Table III provide the effect of P2G technology on the total operation cost of the system and wind power dispatch in comparison with recent studies. As can be seen, wind power dispatch is increased in this case study with respect to recent cases since P2G converts the extra wind power to gas in off-peak hours, and the generated gas is used by natural gas consumers. The operation cost of this case is decreased because this natural gas is produced by extra wind power, which would be lost if it is not used. The operation cost of the system, in this case, is equal to $138794.506.

TABLE III: Operation cost and wind power dispatch in different cases

Cases	Case 1	Case 2	Case 3
Gas system operation cost ($)	134397.039	134898.33	134335.406
Power system operation cost ($)	10207.959	4459.1	4459.1
Total operation cost ($)	144604.998	139357.43	138794.506
Dispatched wind power (MWh)	1429.668	1531.450	1756.619

D. *Case 4: hybrid stochastic IGDT co-optimization for cases 1-3*

Under these circumstances, the uncertainty of residential gas load is considered using IGDT. The operation cost in base condition (i.e., Case 1) equals to $138794.506. The parameter d_r is increased from 0.01 to 0.1 by 0.01 steps to implement the risk-averse strategy of IGDT. As it is obvious from Fig. 6, the robustness function α is boosted, which means that the system operator can tolerate a wider range of gas load uncertainty by the increment of d_r. Also, the operator attains a more robust decision making considering the uncertainty of gas load demand by the increment of robustness parameter d_r. For instance, the robustness function for a value of 0.05 for without the presence of flexible units, is 0.065, which means that a forecast error of 0.065 for gas load unacceptable for the system operator by increasing the operation cost of the network by 5%. Moreover, as can be seen in Fig. 6, the robustness function has greater values in the presence of flexible units that means the system operator can tolerate wider ranges of uncertainty and consequently the uncertainty of gas demand has a lower influence on the operation cost of the system. The effect of robustness function on power generation of units is demonstrated in Fig. 7, which indicates that the power dispatch of gas-fired unit G1 is decreased by the increment of the density of gas pipelines and lack of gas served to this unit.

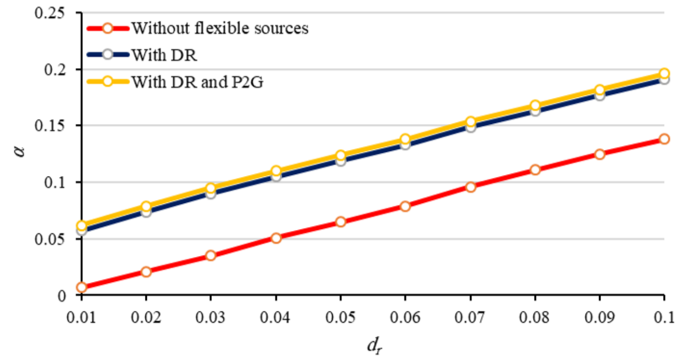

Fig. 6: Variation of robustness optimum function against robustness parameter

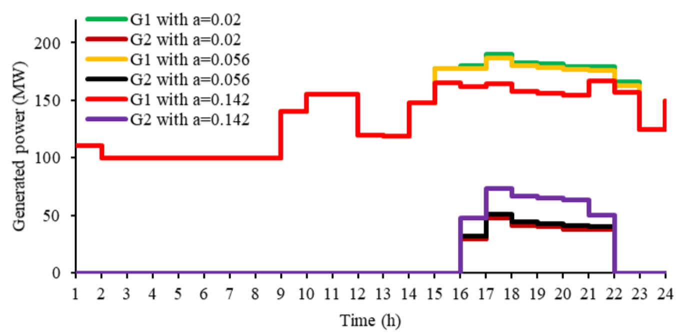

Fig. 7: Power dispatch of units in risk-averse strategy

The opportunity parameter d_ρ is raised from 0.01 to 0.1 to address the risk-seeker strategy, which resulted in a decrease of operation cost from its base condition (i.e., $138794.506). It can be observed from Fig. 8 that the network operator should consider the gas load demand reduction by 4.35% concerning its predicted value to attain an optimistic desirable operation cost of (1-0.03) $134630.671 without considering flexible units. The opportuneness function β has a direct relation with increasing the amount of opportunity parameter d_ρ. Moreover, as can be seen in this figure, when the emerging flexible units are taken into account, the network operator attains to the desired operation cost with a lesser optimistic error concerning the condition that such units do not exist. Indeed, the network operator considers optimistic error in the residential gas load to attain a desirable operation cost of (1-0.04)×$138794.506. Consequently, it results in the decrement of the operation cost belong to the uncertainty associated with the residential gas load demand.

IV. Conclusion

This study proposed a novel hybrid IGDT-stochastic framework for co-optimization of integrated gas and power

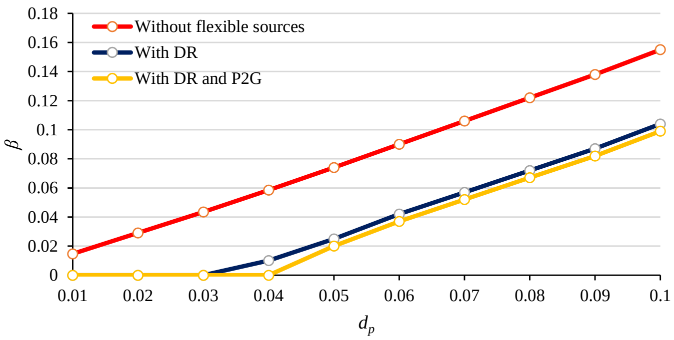

Fig. 8: Variation of opportuneness optimum function against opportunistic parameter

networks with penetration of wind turbines. The proposed model considered uncertainties associated with both gas and power networks, where the uncertainty of power system including wind power output and load demand was modeled using the scenario-based method, and the uncertainty of gas network containing residential gas consumers was estimated by applying IGDT. The proposed hybrid model took advantages of both scenario-based modeling method and IGDT and applied two risk-seeker and risk-averse strategies enabling the network operator to make decisions on system operation with higher inflexibility rate. Moreover, the effect of emerging technologies such as demand response program and power to gas (P2G) unit was studied in the proposed model. The investigation of the presented model provides some remarkable achievements in co-optimization of integrated gas and power networks as follows:

1) The simultaneous consideration of emerging flexible technologies was influential in decreasing total operation cost of the system in comparison with the consideration of such technologies individually.
2) The simultaneous presence of emerging flexible technologies was beneficial in increasing the penetration of wind power in the power system.
3) The network operator reaches the profit regarding the emerging flexible technologies in both risk-averse and risk-seeker strategies in a way that the operator was able to take into consideration the risk against the uncertainty of gas network in risk-averse strategy with the lower cost. Also, the operator benefited from the risk in better condition against the uncertainty in risk-seeker strategy.

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